Virtual Arm with Multimodal Biased feedback for Improving EEG Motor Imagery Calibration Training

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1. Introduction

1.1 Motor Imagery & Issues

One of the most researched applications of the Brain-Computer Interface (BCI) is its use in motor restoration and motor rehabilitation. By means of assistive technologies such as prosthesis, stimulators or robotic exoskeletons controlled by a BCI, the lost motor function can be regained [1].

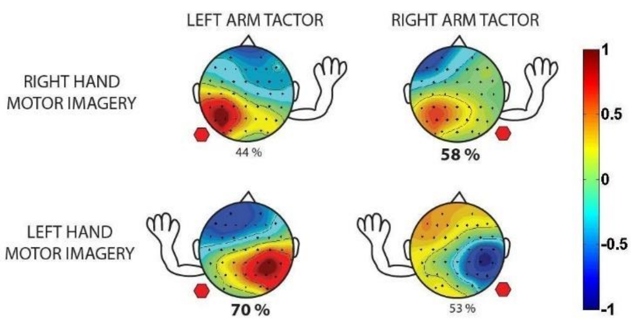


Figure 1: Different MI tasks produce different brain waves spatially [13]

As shown in Figure 1, different motor imagery tasks produce different EEG signals that can be monitored. This information can be interpreted and fed into BCI-controlled prosthetics in order to assist the user in the physical task, encouraging restoration of the lost motor function.

However, training a person to accurately communicate with a Motor Imagery BCI is a difficult task that requires several training sessions spanning across weeks. This is known as BCI illiteracy [2]. Training is required as EEGs read event-related-desynchronization (ERD) and event-related-synchronization (ERS) brain waves. These ERD and ERS waves vary across subjects, thus calibration is needed for each individual.

Motor Imagery (MI) based BCIs demand particularly longer training since the mental rehearsal of a movement without performing it, is a counterintuitive task for majority of individuals. Most users cannot visualize a vivid picture of the movement and its kinesthetic experience [3].

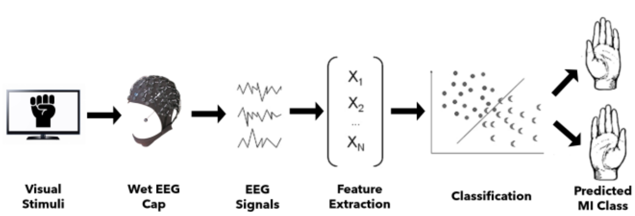


Figure 2: General Open MI Calibration System [Modified from 14]

Traditional training protocols include execution of a MI task by the user, followed by arrows on a screen as an indicator of which task to carry out, known as visual stimuli. This is shown in Figure 2. However, an imaginary action can range from the visualization of a self-performed movement from a first-person to a third person view of the movement, along with other forms of visualization the subject may have [4]. Although such types of MI tasks all involve voluntary actions, they may not involve similar cognitive processes for a myriad of reasons, largely attributed to "vagueness of instruction". This introduces a large amount of inter-subject variability, greatly reducing accuracy of BCIs.

Evidently, to expand the applications BCI has in neurorehabilitation, its training time must be reduced. One such issue contributing to extended training time is that the presentation of feedback is temporally incongruent with the subject's mental image of a bodily movement. This introduces additional variance across subjects, resulting in more data required for BCIs to meet the level of accuracy desired.

In the training paradigm introduced by Pfurtscheller and Neuper [5], subjects imagined either a left-hand or right-hand movement and watched a horizontal feedback bar on a computer screen that was extended to the right or to the left based on the classifier output. This design has been replicated and used in majority of research conducted within this field of study. However, the feedback design currently being employed has no congruity with the type of image that the subjects held (image of a bodily hand or a foot). Not only does the disparity between the visual feedback and the type of image confuse the subjects during the task, but it also prevents them from imagining the kinesthetic experience and correcting their imagery strategy.

1.2 Ongoing Research

Currently, there has been ongoing recent research of android-like arms being used as a visual stimulus [6]. By observing the real-time movement of the robotic arm, subjects can unambiguously perform the MI task, leading to higher training performance and accuracy. We hypothesize that by combining the use of a virtual robotic arm as visual stimuli together with mirror therapy and biased feedback, we can achieve better MI training performance and accuracy, while making it financially accessible to all.

Mirror therapy exploits the brain's preference to prioritize visual feedback over somatosensory or proprioceptive feedback concerning limb position first devised by Ramachandran and Rogers-Ramachandran [7]. The visual feedback from viewing the reflection of the intact limb in place of the phantom limb made it possible for the patient to perceive movement in the phantom limb. Thus, we use the principle of mirror therapy to aid participants in imagining the kinesthetic experience.

It has been shown that biased self-regulation of motor imagery features can improve in relation to positive bias of feedback [8]. In our experiment, we combine the use of the virtual arm with mirror therapy and biased feedback, to improve subject embodiment and decrease ambiguity to achieve higher MI training performance and accuracy.

2. Hypothesis & Objective

We hypothesise the abstractness of simple visual stimuli, such as arrows, cause heterogeneous imaginations across users, compromising calibration accuracy due to inter-subject variability.

Additionally, we hypothesise using a virtual arm and multimodal biased feedback to demonstrate the task makes training more interesting, intuitive, and reduces inter-subject variability, and predict a 5-10% accuracy improvement. With similar ERD & ERS responses across individuals, our ML model will be able to train with others' EEG data, resulting in reduced calibration time.

3. Experiment Design & Protocol

Bear in mind methodology is split into 2 sections, experiment design & protocol, and data collection & analysis.

The experiment is divided into 2 sessions each lasting ~30 minutes. In session 1, participants are shown the standard visual stimuli for their MI tasks. In session 2, participants are instead shown a video of a virtual arm as visual stimuli. Otherwise, both sessions are identical. Before both sessions, the subject is briefed on what they can expect, and shown short snippets of the experiment.

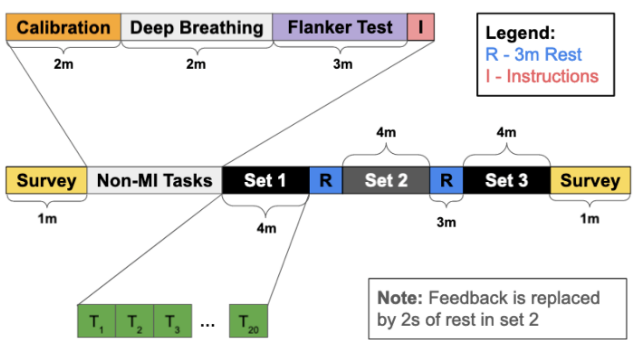


Figure 3: Block Diagram of Sessions 1 & 2

We will group the tasks into 2 broad categories: Non-MI tasks & MI tasks:

Non-MI Tasks	MI Tasks
Calibration	MI Task Classes
Deep Breathing	Biased Feedback
Flanker Attention Test	Visual Stimuli

Pre-experiment survey & post-experiment survey will not be discussed here, as it is a simple google forms. A summary of the results, and more details on each task are included in the appendix.

3.1 Non-MI Tasks

Calibration The participant closes their eyes and relax for 60s, thinking of nothing, followed by a short break. They then repeat the same procedure, instead opening their eyes this time. This is required as a baseline reading, to help remove background artifacts from the EEG signals, and identify brainwaves related to ERS and ERD.

Deep Breathing A short breathing animation is played. This helps the user relax, clear one's mind of any lingering thoughts, and captures the user's current inattention level.

Flanker Attention Test Subjects are told to complete multiple reaction tests, with the aim of accuracy and speed. This activity helps the user focus before MI tasks, get used to visual stimuli on the screen, and captures the user's current attention level.

3.2 MI Task Trials

There are 3 sets of tasks, each consisting of 20 trials. Each trial starts with 4s of fixation cross to maintain focus, 8s of a random MI task, and ends with a 2s rest. At the end of each set of 20 trials, there is a 3-minute break, and participants can continue whenever they want afterwards.

We will be using 5 classes of MI tasks:

- **L**: Moving (right hand) leftwards
- **R**: Moving (right hand) rightwards
- **F**: Reaching (right hand) out/forward
- **C**: Clenching & unclenching (right fist)
- **X**: Resting, no movement

The 20 trials are split into 5 groups, with each group assigned to a different MI task.

3.3 Biased Feedback

At the end of each trial in set 1 & set 3, biased feedback is given to the subject for further motivation. This feedback is pre-computed. Around 30% are positive feedback, 50% are neutral feedback and 20% being negative feedback. The feedback is shown during the 2s break after every trial. Set 2 has no feedback.

3.4 Session 1 Visual Stimuli: Symbols

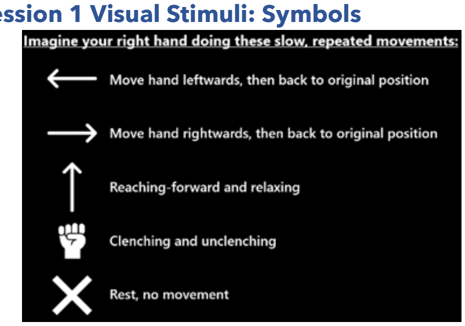


Figure 4: Visual Stimuli

Session 1 serves as our control. We used standard left and right arrows to signal imagining moving their right arm left and right. Due to a lack of symbols to represent reaching out an up arrow was used, and subjects were reminded to imagine moving their right arm out and not up. A fist emoji/symbol was used to represent clenching and a X was used to represent rest (imagine holding your arm still)

During set 2, the 2s of feedback are replaced by 2s of rest where a blank screen is shown. Otherwise, each trial follows the format of 4s fixation (fixate on a fixation cross), 8s of task (the screen just shows a symbol), 2s of feedback as shown in the diagram below.

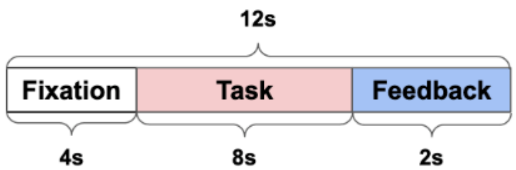


Figure 5: Block Diagram for Session 1 MI Tasks

3.5 Session 2 Visual Stimuli: Virtual Arm

Figure 6: Screenshot of the "fist" animation

The virtual arm was constructed using popular and free 3D modeling and animation software Blender. The pre-rigged body was taken from turbosquid.com [9] under the standard 3D Model License [10].

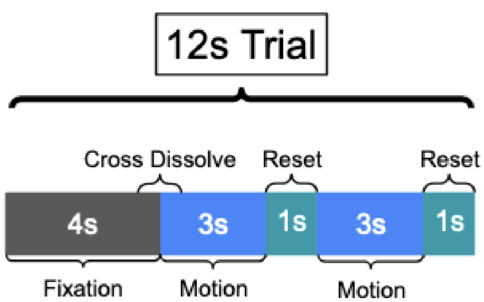


Figure 7: Block Diagram for Session 2 MI Tasks

Each trial (Imagination session) lasted 12s, of which the first 4s were spent fixating on the fixation cross. Close to the last second of fixation the fixation cross dissolved into the arm performing the motion. This was implemented to minimize cuts which may distress or otherwise jar the subjects.

The 4s of fixation was followed by 3s of the arm performing the motion which was then followed by the arm going bac to the original position (reset) in 1s. Which was then followed by another 3s of motion and the 1s of the arm resetting. To place emphasis on the desired motion a 3s motion to 1s reset ratio was chosen.

Figure 8: Screenshot of the "right" animation

The animated body was mirrored (subjects are instructed to imagine moving their right arm) to make it easier for the subjects to imagine and to potentially evoke some mirror therapy effects. The body was placed towards the left of the screen to allow a more zoomed in shot while making sure that the moving arm stays in in frame.

Inverse kinematics are often used to produce natural looking animations, an attempt was made to implement inverse kinematics however due to a repeated shoulder buckling issues we opted to use basic keyframe animations moving each joint by hand plus some acceleration and deceleration. This technique was sufficient in making natural looking animations for our research as we mainly focused on simple cores movements.

The brightness of the animations was minimized to avoid jarring the subjects and minimize stress on their eyes as lights were turned off during the experiment.

In addition to having a solid grey background, shadows were minimized to improve focus.

Note: Each trial is followed by 2s of rest/feedback bringing the total trial length to 14s

4. Data Collection & Analysis

4.1 Participants & Recordings

We have recruited 13 participants (12 male, 1 female) to take part in both sessions of our experiment, all of which were high school students who gave written informed consent and received monetary compensation for their participation. All subjects were right-handed, and none suffered from any physical disabilities.

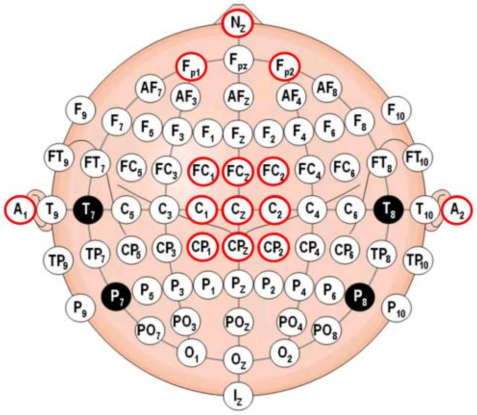


Figure 9: Diagram of EEG Channels

A wet EEG cap was used in this experiment. A total of 14 channels were used – **NZ, A1, A2, Fp1, Fp2, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4**. An extra electrode is used to serve as electrical ground. The channels were sampled at $1000Hz$.

4.2 Experimental Setup

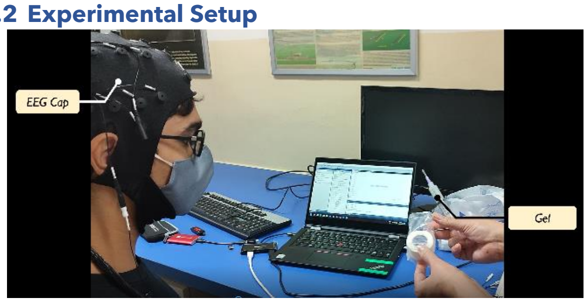


Figure 10: Setting up wet EEG cap before experiment

Prior to the experiment, electrically conductive gel was injected into the respective electrodes with a syringe to help improve the resolution of brain signal readings. 14+1 electrodes were used, with one taped onto each ear (A1, A2), a third taped onto the forehead of the subject (X1), and the rest positioned on the wet EEG cap. Each electrode is adjusted accordingly to minimize impedance readings and improve signal to noise ratio. Only impedance readings below $50k\Omega$ were accepted, with most readings $< 1k\Omega$.

Note: All Impedance readings are available in appendix

Figure 11: Experimental Set-up

Our experimental set-up consists of a display, low-latency controls to record timestamps accurate to the millisecond, an EEG cap to record the subject's brain waves, and a Tobii eye tracker to ensure the subject is paying attention to the screen. Lights were turned off during the experiment and turned on purely for photographic purposes in the image above.

4.3 Data Collection

The experiment is fully automated and paced by a Python program we created and made use of a popular open-source library PsychoPy [11]. It displays on-screen instructions and visual stimuli required for MI tasks, and communicates with the EEG cap, creating stim code timings to aid data analysis while saving local log files detailing local time stamps correlating with the user's pace. This allows for us to match up the EEG's timestamps with PsychoPy's.

Raw data collected:

1) PsychoPy log files with (computer) timings
2) EEG timeseries with stim code timings

4.4 Data Processing

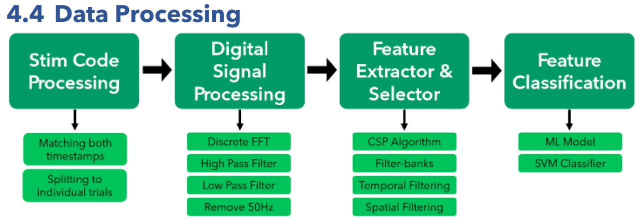


Figure 12: Post Processing Procedure

Only offline processing is carried out after the experiment is completed, and no processing occurs in real-time.

4.4.1 Stim Code Processing

The PsychoPy program sends Stim Code timestamps to the EEG amplifier whenever a new section in the experiment procedure starts and is then used to synchronize the EEG timeseries data with PsychoPy's timestamps. Afterwards, the timeseries needs to be subdivided into smaller timeseries, each representing EEG signal data for a MI trial, to be fed into the signal processor.

4.4.2 Digital Signal Processing

Before we can use the EEG data to identify ERD and ERS signals, we must first remove noise. This step is largely handled by the Filter Bank Common Spatial Patterns (FBCSP) Toolbox [12]. A discrete Fast Fourier Transform (FFT) is applied onto the timeseries to translate it to the frequency domain, and we apply a high & low pass filter, as well as a 50 Hz filter to remove unwanted noise.

Note: 50Hz is the frequency of Singapore's wall AC power supply, which could generate some EMI, distorting EEG brain signal readings.

4.4.3 Feature Extractor & Selector

The built-in CSP algorithm in the FBCSP Toolbox helps take care of feature extraction & selection from our processed EEG signals, to extract out ERD and ERS brain signals correlated with MI tasks.

4.4.4 Feature Classification

We create a Support Vector Machine (SVM) based ML Model to read the ERD and ERS brain signals and classify them into the 5 classes of MI tasks. This essentially allows our EEG cap to identify which of the 5 classes the subject is imagining for his/her MI task.

75% of the trials were used as a learning dataset to train the ML Model, while 25% of the trials were used as a validation dataset to identify the ML Model's accuracy.

We compute binary (2-class) classification accuracy between the "relax" class & all 4 other MI classes. This provides a fair comparison of whether feedback improves performances or not for each MI classes (**L,R,F,C**).

A 5-fold CV is used for subject-dependent cross-validation, so each subject's accuracy is computed independently. This means we will have a 2D table of accuracy, with an accuracy term for each subject & each of the 4 MI classes. This allows us to compare accuracies across subjects and MI class and reach various conclusions.

5. Results & Discussion

5.1 Classification Accuracies Across Subjects

Class	C	X	L	R	F
Accuracy (%)	98.8462	97.6923	98.8462	98.2692	99.8077

Figure 13: Accuracies of each MI class, averaged across all individuals

From our ML Model, we have the table of accuracies for each MI task. Data from both sessions and all 3 trials have been combined for each subject and split between validation & training dataset for the ML Model. After getting the accuracy table for each subject, we average the values to get the table above.

5.2 Statistical Significance Testing

We have run our ML Model 3 more times (starting off without any pre-trained data), this time on each of the 3 sets of 20 trials. We combine the accuracy values from sets 1 & 3 to get 104 samples of accuracy for "trials with biased feedback", and from set 2, 52 samples of accuracy for "trials without biased feedback". Since they are sampled from 2 different distributions, we conduct a 2-Sample t-Test to determine if the distributions have different means.

Variables:

Let μ_2 be the true mean of the distribution of accuracies of trials from set 2

Let μ_{1+3} be the true mean of the distribution of accuracies of trials from set 1 & 3.

Let the significance level be 0.5%.

Hypothesis:

$$H_0: \mu_{1+3} = \mu_2$$

$$H_a: \mu_{1+3} > \mu_2$$

SRS: A SRS was conducted to pick the trials used as part of the validation dataset.

Normality: Both populations (Set 2 & Set 1 + Set 3) have a sample size larger than 30. By Central Limit Theorem, both populations are normally distributed.

Independence: It is reasonable to assume all EEG readings are independent of one another.

To test the hypothesis H_0, we compute the 2-sample t statistic and p-value:

2-Sample t-Test: Assuming Unequal Variances		
Value	**Set 1 + Set 3**	**Set 2**
Mean	0.6039663	0.54367
Variance	0.0217393	0.016123
Sample Size	104	52
df	117	
t Stat	2.6464932	
P(T<=t) one-tail	0.0046262	
t Critical one-tail	1.6579817	

Figure 14: 2-Sample t-Test results

As the one-tailed t-value is 0.004<0.005, at the 0.5% significance level, we can conclude that the presence of biased feedback helped improve the accuracy of classification. We theorize this is due to the feedback encouraging the user, causing the subject to focus better and produce more distinct brainwaves.

Note: The full accuracy tables for each set of 20 trials is found in the Appendix.

5.3 Limitations

However, as limited MI trials were executed by each user we cannot conclude with as much certainty as we hoped that our new form of stimuli is significant better.

Additionally, all our subjects are high-school students and largely male, unrepresentative of the general population.

We originally planned to use a physical robotic arm, however due to technical issues we unable to construct it in time thus we resorted to a virtual robotic arm which may not be as interactive and engaging as a physical robotic arm.

Furthermore, our accuracy may have been limited by the use of SVMs, with more time and data we hope to implement deep learning using KCNNs.

5. Conclusion

Our research shows that biased multimodal feedback is extremely effective in boosting MI BCI classification performance in the case of large cores movements such as moving the right arm left and right in large sweeping motions, which may be sufficient to prompt further investigation of its applications in fine motor movements.

6. Future Work

Previously, we have mentioned that all EEG brain signal data processing occurs offline. However, with our already trained parameters for our ML Model classifier, with enough computing power, in the future, we could possibly use it to predict which class the subject is executing for the MI task in real time. This could be a big leap forward in technological progress, and allow for BCIs to pave the way for motor restoration and motor rehabilitation.

Additionally, with our limited data, we cannot reliably identify the accuracy of each feedback type. This requires more subjects and trials for each section, and an additional mapping of feedback type during 5-fold CV in our ML Model.

Appendix

Classification Accuracies Across Subjects

Session 1 & Session 2 data is combined before being fed into the model.

Set 1 of 20 MI trials

No.	relax Vs clench	relax Vs left	relax Vs right	relax Vs forward
1	0.604167	0.708333	0.520833	0.333333
2	0.5625	0.541667	0.458333	0.479167
3	0.791667	0.916667	0.770833	0.6875
4	0.708333	0.541667	0.770833	0.6875
5	0.75	0.4375	0.729167	0.583333
6	0.5625	0.583333	0.770833	0.666667
7	0.5	0.541667	0.5	0.583333
8	0.75	0.9375	0.666667	0.604167
9	0.520833	0.479167	0.416667	0.5625
10	0.5	0.625	0.729167	0.6875
11	0.541667	0.541667	0.875	0.9375
12	0.75	0.8125	0.916667	0.479167
13	0.625	0.8125	0.5	0.4375

Set 2 of 20 MI trials

No.	relax Vs clench	relax Vs left	relax Vs right	relax Vs forward
1	0.5625	0.645833	0.416667	0.4375
2	0.458333	0.770833	0.604167	0.541667
3	0.479167	0.458333	0.479167	0.5625
4	0.625	0.333333	0.583333	0.583333
5	0.458333	0.479167	0.4375	0.645833
6	0.666667	0.4375	0.541667	0.770833
7	0.75	0.416667	0.416667	0.291667
8	0.458333	0.541667	0.5	0.75
9	0.458333	0.416667	0.583333	0.541667
10	0.375	0.5	0.666667	0.479167
11	0.541667	0.5625	0.583333	0.395833
12	0.8125	0.604167	0.854167	0.645833
13	0.4375	0.583333	0.395833	0.729167

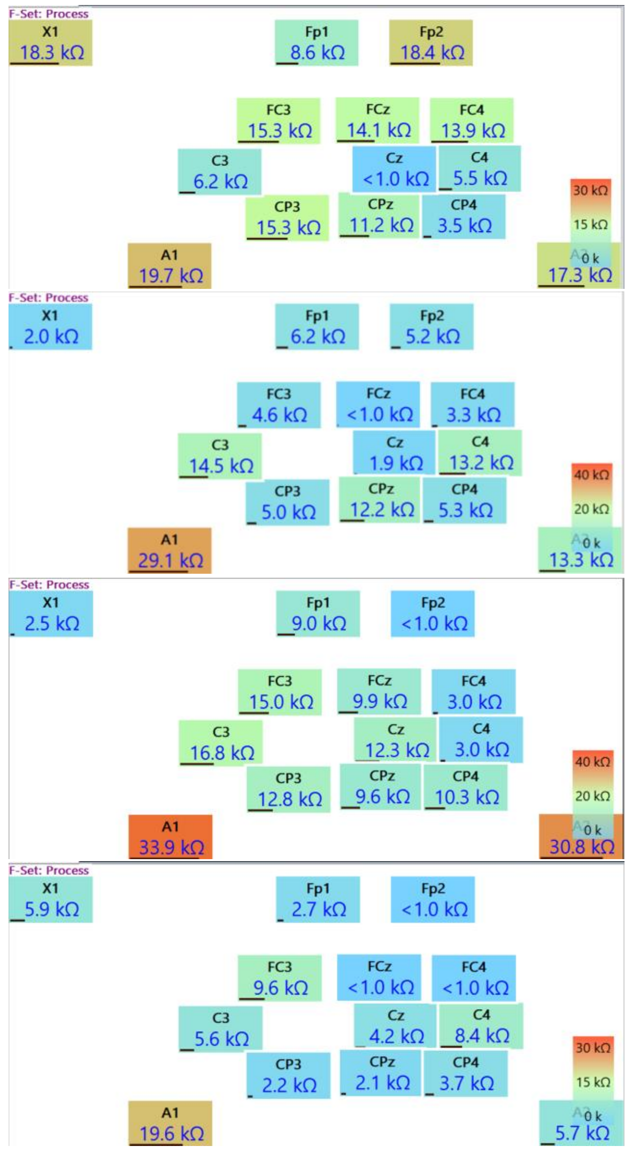
Set 3 of 20 MI trials

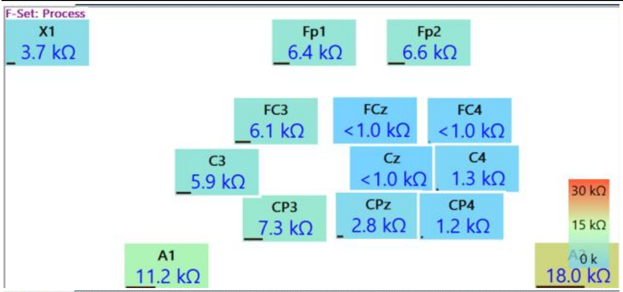
No.	relax Vs clench	relax Vs left	relax Vs right	relax Vs forward
1	0.666667	0.5	0.75	0.458333
2	0.604167	0.645833	0.625	0.5
3	0.645833	0.708333	0.5	0.666667
4	0.6875	0.729167	0.583333	0.541667
5	0.291667	0.541667	0.666667	0.75
6	0.541667	0.75	0.8125	0.479167
7	0.5625	0.583333	0.520833	0.583333
8	0.416667	0.4375	0.583333	0.5625
9	0.458333	0.4375	0.458333	0.25
10	0.625	0.5	0.520833	0.583333
11	0.916667	0.541667	0.520833	0.6875
12	0.791667	0.958333	0.458333	0.5625
13	0.458333	0.375	0.354167	0.458333

Impedance Readings

Impedance readings measured wrt. Ground electrode

Session 1

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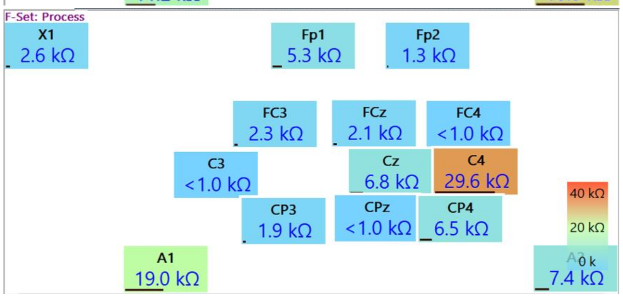
Fp1 6.4 kΩ
Fp2 6.6 kΩ
FC3 6.1 kΩ
FCz <1.0 kΩ
FC4 <1.0 kΩ
C3 5.9 kΩ
Cz <1.0 kΩ
C4 1.3 kΩ
CP3 7.3 kΩ
CPz 2.8 kΩ
CP4 1.2 kΩ
30 kΩ
15 kΩ
0 k
A1 11.2 kΩ
18.0 kΩ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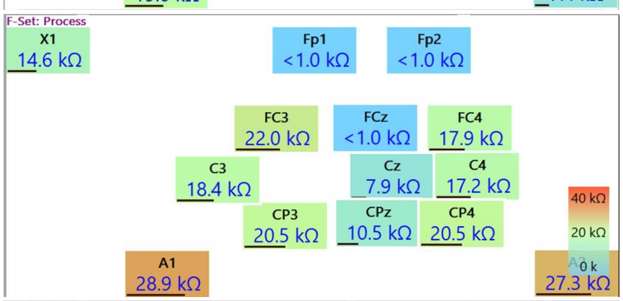
Fp1 5.3 kΩ
Fp2 1.3 kΩ
FC3 2.3 kΩ
FCz 2.1 kΩ
FC4 <1.0 kΩ
C3 <1.0 kΩ
Cz 6.8 kΩ
C4 29.6 kΩ
CP3 1.9 kΩ
CPz <1.0 kΩ
CP4 6.5 kΩ
40 kΩ
20 kΩ
0 k
A1 19.0 kΩ
7.4 kΩ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Fp2 <1.0 kΩ
FC3 22.0 kΩ
FCz <1.0 kΩ
FC4 17.9 kΩ
C3 18.4 kΩ
Cz 7.9 kΩ
C4 17.2 kΩ
CP3 20.5 kΩ
CPz 10.5 kΩ
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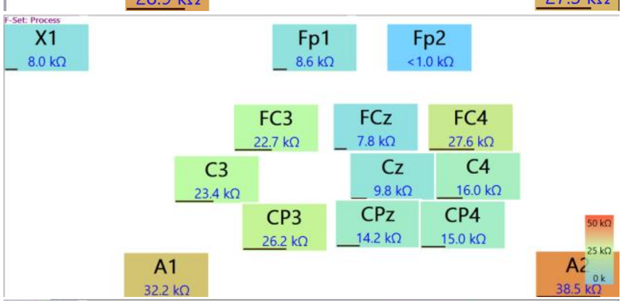
20 kΩ
0 k
A1 28.9 kΩ
27.3 kΩ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Fp1 8.6 kΩ
Fp2 <1.0 kΩ
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FCz 7.8 kΩ
FC4 27.6 kΩ
C3 23.4 kΩ
Cz 9.8 kΩ
C4 16.0 kΩ
CP3 26.2 kΩ
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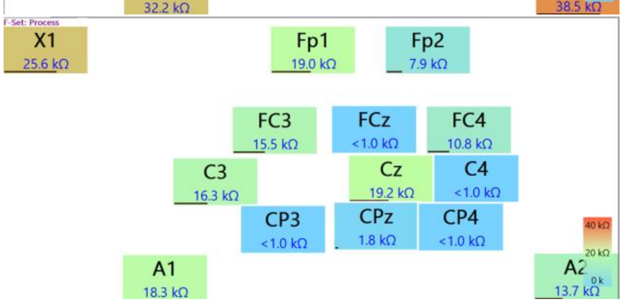
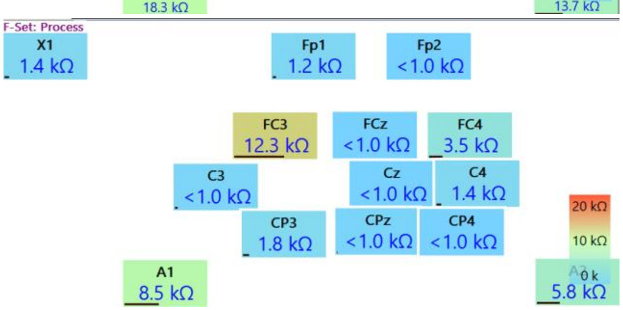
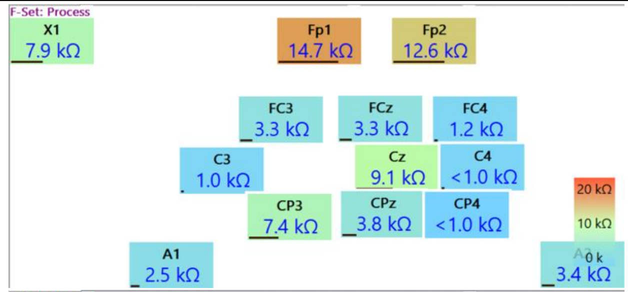
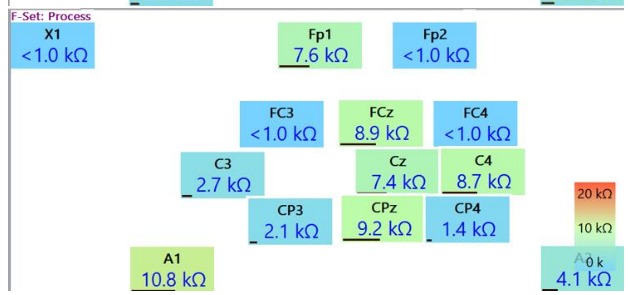
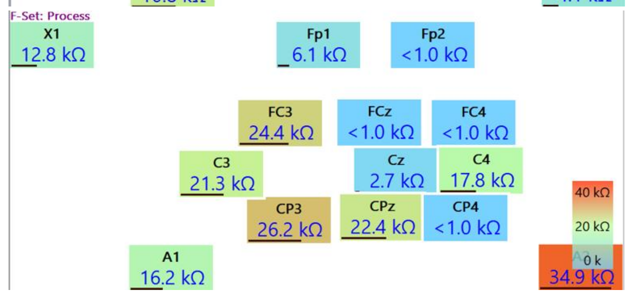
A2 38.5 kΩ


F-Set: Process
X1 25.6 kΩ
Fp1 19.0 kΩ
Fp2 7.9 kΩ
FC3 15.5 kΩ
FCz <1.0 kΩ
FC4 10.8 kΩ
C3 16.3 kΩ
Cz 19.2 kΩ
C4 <1.0 kΩ
CP3 <1.0 kΩ
CPz 1.8 kΩ
CP4 <1.0 kΩ
40 kΩ
20 kΩ
0 k
A1 18.3 kΩ
A2 13.7 kΩ

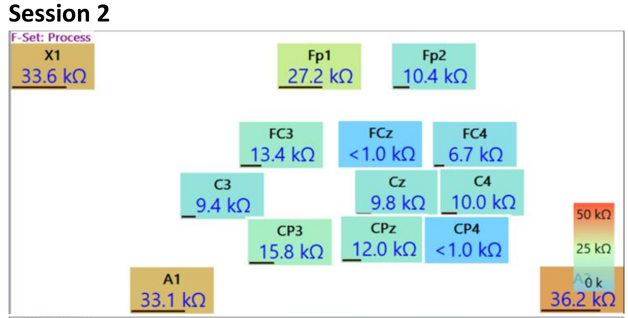

F-Set: Process
X1 1.4 kΩ
Fp1 1.2 kΩ
Fp2 <1.0 kΩ
FC3 12.3 kΩ
FCz <1.0 kΩ
FC4 3.5 kΩ
C3 <1.0 kΩ
Cz <1.0 kΩ
C4 1.4 kΩ
CP3 1.8 kΩ
CPz <1.0 kΩ
CP4 <1.0 kΩ
20 kΩ
10 kΩ
0 k
A1 8.5 kΩ
5.8 kΩ

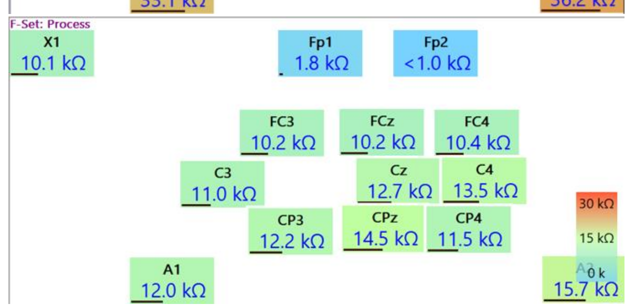

F-Set: Process
X1 7.9 kΩ
Fp1 14.7 kΩ
Fp2 12.6 kΩ
FC3 3.3 kΩ
FCz 3.3 kΩ
FC4 1.2 kΩ
C3 1.0 kΩ
Cz 9.1 kΩ
C4 <1.0 kΩ
CP3 7.4 kΩ
CPz 3.8 kΩ
CP4 <1.0 kΩ
20 kΩ
10 kΩ
0 k
A1 2.5 kΩ
3.4 kΩ

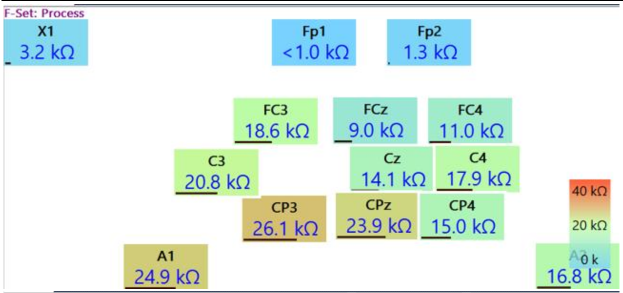

F-Set: Process
X1 <1.0 kΩ
Fp1 7.6 kΩ
Fp2 <1.0 kΩ
FC3 <1.0 kΩ
FCz 8.9 kΩ
FC4 <1.0 kΩ
C3 2.7 kΩ
Cz 7.4 kΩ
C4 8.7 kΩ
CP3 2.1 kΩ
CPz 9.2 kΩ
CP4 1.4 kΩ
20 kΩ
10 kΩ
0 k
A1 10.8 kΩ
4.1 kΩ

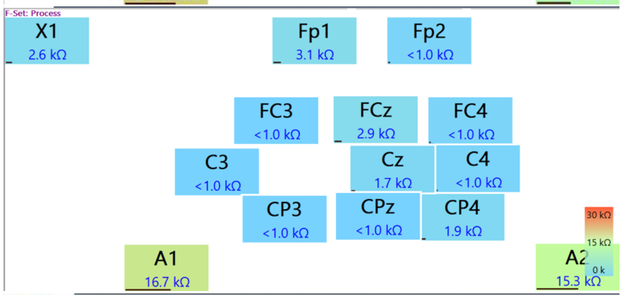

F-Set: Process
X1 12.8 kΩ
Fp1 6.1 kΩ
Fp2 <1.0 kΩ
FC3 24.4 kΩ
FCz <1.0 kΩ
FC4 <1.0 kΩ
C3 21.3 kΩ
Cz 2.7 kΩ
C4 17.8 kΩ
CP3 26.2 kΩ
CPz 22.4 kΩ
CP4 <1.0 kΩ
40 kΩ
20 kΩ
0 k
A1 16.2 kΩ
34.9 kΩ

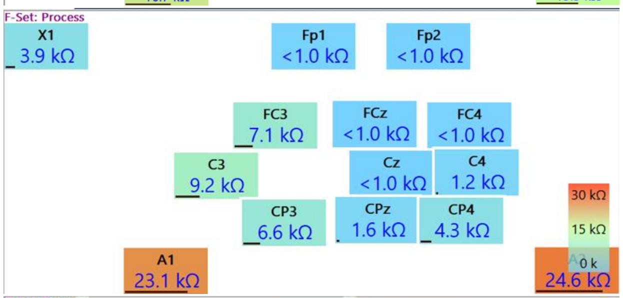
Session 2

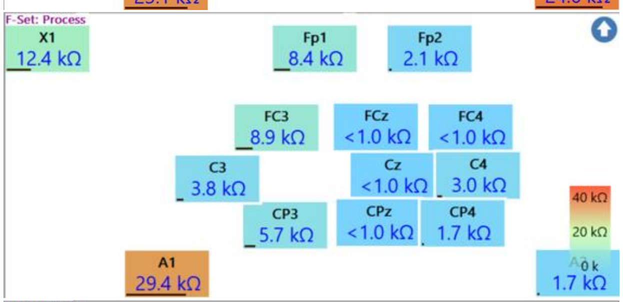

F-Set: Process
X1 33.6 kΩ
Fp1 27.2 kΩ
Fp2 10.4 kΩ
FC3 13.4 kΩ
FCz <1.0 kΩ
FC4 6.7 kΩ
C3 9.4 kΩ
Cz 9.8 kΩ
C4 10.0 kΩ
CP3 15.8 kΩ
CPz 12.0 kΩ
CP4 <1.0 kΩ
50 kΩ
25 kΩ
0 k
A1 33.1 kΩ
36.2 kΩ

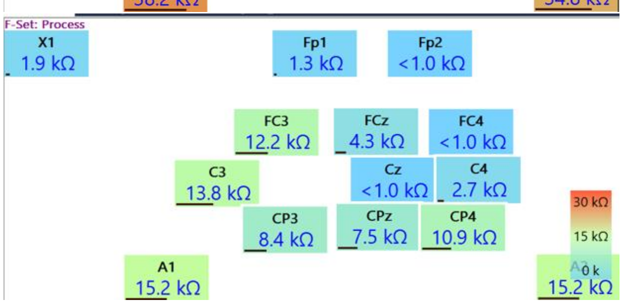

F-Set: Process
X1 10.1 kΩ
Fp1 1.8 kΩ
Fp2 <1.0 kΩ
FC3 10.2 kΩ
FCz 10.2 kΩ
FC4 10.4 kΩ
C3 11.0 kΩ
Cz 12.7 kΩ
C4 13.5 kΩ
CP3 12.2 kΩ
CPz 14.5 kΩ
CP4 11.5 kΩ
30 kΩ
15 kΩ
0 k
A1 12.0 kΩ
15.7 kΩ

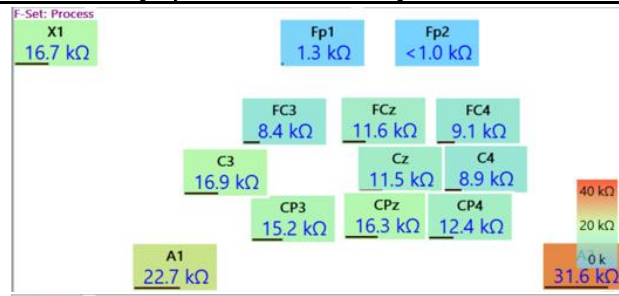


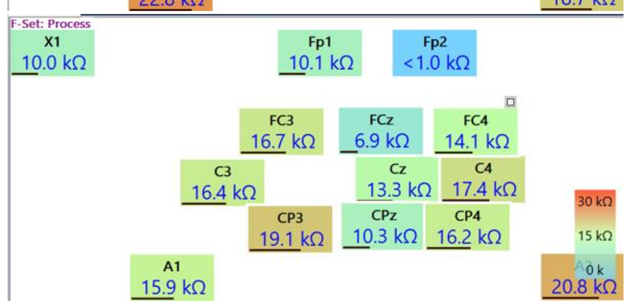






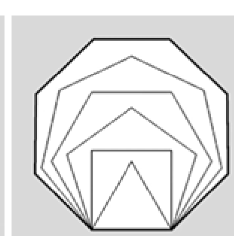






PsychoPy Program Screenshots

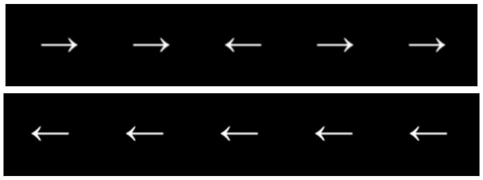
Deep Breathing



Screenshots of Deep Breathing Animation

Together with audio instructions, user breathe in and out, in sync with the expansion and contraction of the graphic.

Flanker Attention Tests

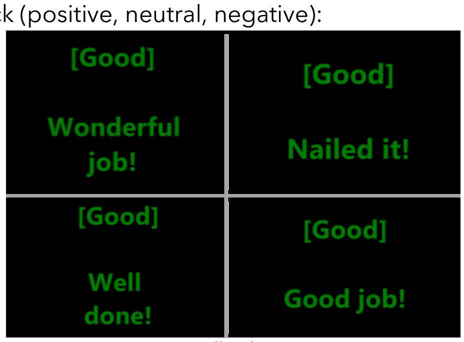


Screenshots of Flanker Attention Test

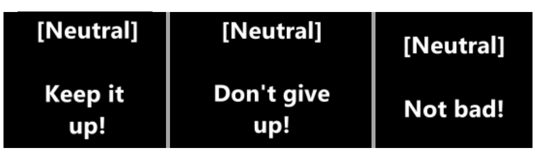
Subjects complete as many flanker trials as possible within in the 180s period. For each flanker trial, 5 arrows either pointing left or right are displayed (Figure 5). If majority of arrows point left, the subject must press the left key, else it will be considered a failure, and vice versa.

Biased Feedback

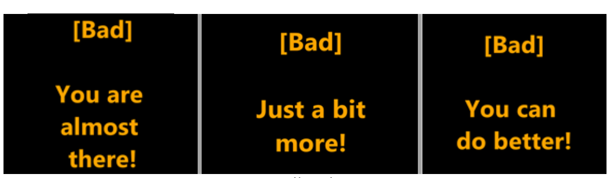
There are multiple different messages for each type of feedback (positive, neutral, negative):



Positive Feedback Messages



Neutral Feedback Messages



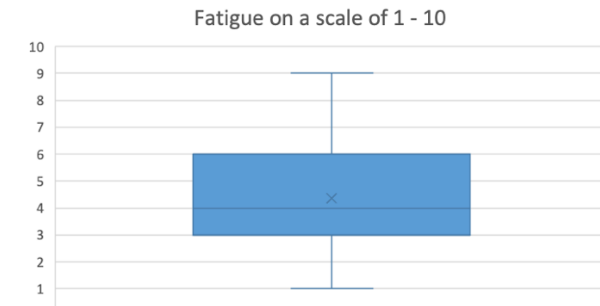
Negative Feedback Messages

The exact message for each type of feedback is randomly chosen.

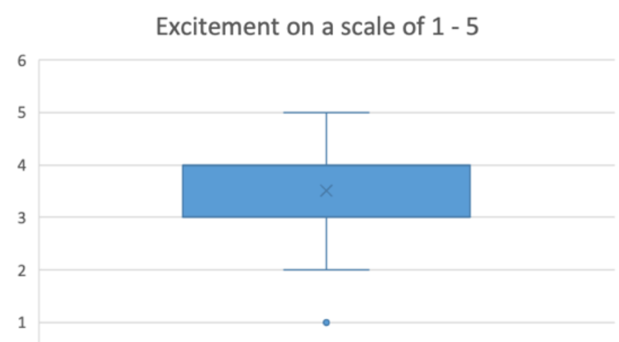
Pre-Experiment Survey

Participants are given a QR code to a short Microsoft form to complete. Questions include:

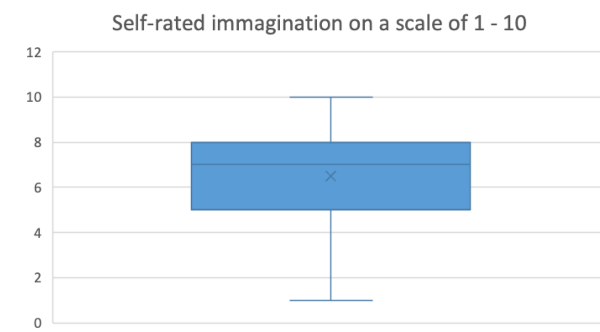
- Fatigue level before the experiment.



- How excited they are for the experiment.



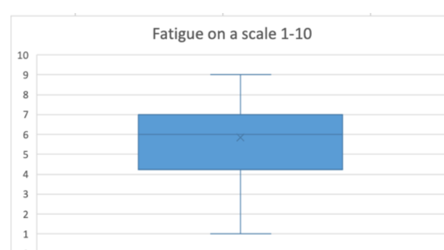
- Self-rated imagination/ visualization capabilities.



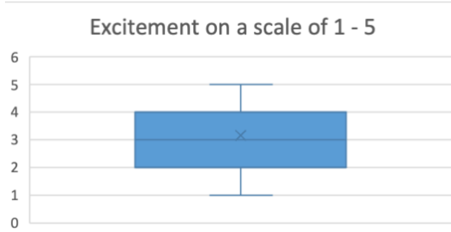
Post-Experiment Survey

Participants are given a QR code to a short Microsoft form to complete. Questions include:

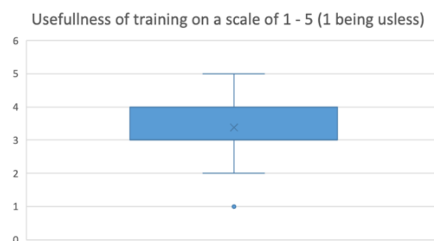
- Fatigue level right after the experiment.



- What they felt would be an optimal duration of each session.
  - Responses: 20 - 45 mins
- How exciting they felt the training was.



- Aspects of the experiment they didn't like.
    - Popular responses
        - Repetitive
        - Bored during breaks
        - No major discomfort
        - No backrest
- How much they think they improved their imagination capabilities compared to before the experiment.



- What they were thinking of during training.
    - Popular responses
        - Moving
        - Actions in my head
        - Right hand
        - Hand is electric
- How they found the pace of the experiment.
    - Popular responses
        - Ok
        - Just nice
- Challenging aspects of the experiment.
    - Popular responses
        - Dealing with fatigue towards the end
        - Reputedly focusing and imagining was hard
- Thoughts on the visual stimuli provided
    - Popular responses
        - It was fine
        - The visual stimuli were a little distracting.
        - It was very useful for me to imagine
- Additional feedback
    - Breathing exercise was too long and had too much time between breath in and out

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Literature Review

1. Overview - Introduction to Modern Brain-Computer Interface Design - Christian A. Kothe
2. Implementation of a Motor Imagery based BCI System using Python Programming Language
3. Low-Cost Robotic Guide Based on a Motor Imagery Brain–Computer Interface for Arm Assisted Rehabilitation
4. Deep learning with convolutional neural networks for brain mapping and decoding of movement-related information from the human EEG
5. A conceptual space for EEG-based brain-computer interfaces
6. Brain computer interfacing: Applications and challenges
7. Converging Robotic Technologies in Targeted Neural Rehabilitation: A Review of Emerging Solutions and Challenges
8. A Comprehensive Review on Critical Issues and Possible Solutions of Motor Imagery Based Electroencephalography Brain-Computer Interface
9. Bringing Together Robotics, Neuroscience, and Psychology: Lessons Learned From an Interdisciplinary Project
10. Combination of high-frequency SSVEP-based BCI and computer vision for controlling a robotic arm
11. Machine-learning-based coadaptive calibration for brain-computer interfaces
12. EEG Based Brain Computer Interface for Controlling a Robot Arm Movement Through Thought